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# Improving empirical storm damage models by coupling with high-resolution gust speed data

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ABSTRACT

Empirical forest storm damage models can assist in identifying the key factors of the occurrence of storm damage in order to develop locally adapted measures to minimize damage in forests. Yet, there is a significant lack of knowledge in these models concerning the correlation between storm damage and high-impact near-surface airflow. To improve our understanding in this field, we built Random Forests (RF) and Generalized Linear Models (GLM) for evaluating the association between high resolution gust speed data and long-term, multi-event forest storm damage data from long-term permanent forest growth and yield plots. The tested gust speed data were derived from two different gust speed models: a numerical non-hydrostatic mesoscale model and a statistical model.

In all RF and GLM models gust speed was a statistically significant predictor. The performance of the evaluated empirical models was very high (area under the receiver operating characteristic curve values AUC = 0.86–0.99). Depending on the type of model, the relative importance of gust speed was moderate to very high (up to 35%). However, starting from models using all significant predictors and excluding gust speed, the performance loss was almost negligible in all models. Furthermore, modeling long-term storm damage for each storm event individually performed better compared to modeling average long-term, event-unspecific storm damage.

Our results demonstrate that empirical storm damage models using only gust speed as a predictor can reach moderate (GLM) to very high (RF) performance, even without any other information on terrain and forest attributes. However, if detailed terrain and forest data are available, empirical storm damage models may have such a high performance that adding gust speed data improves them very little. The correlation between gust speed and storm damage in the coupled modeling system is a fundamental first step in being able to evaluate potential changes of forest storm damage in a changing climate with potentially changing wind regimes. Additionally, further improvements could be achieved by improved representation of airflow in complex forest.

## 1. Introduction

Strong winds and storms are potential agents leading to sudden forest ecosystem changes and are referred to as fast-driven natural disturbance (Thom et al., 2013). While in unmanaged or natural forests this type of disturbance is simply a change in ecosystem status with many ecological implications (Ulanova, 2000), storms can lead to decisive economic damage in managed forests. Among the many undesired effects in managed forests are losses in harvestable timber, depreciation of wood quality of salvaged stems, potentially increased harvesting costs and potential breakdown of the timber market (Prestemon and Holmes, 2008). In many areas of the world, storm damage is a predominant disturbance agent (Schelhaas et al., 2003; Studholme, 1995).

For both natural and managed forests, empirical storm damage models help estimate the effects of disturbance by storms. They can identify key factors frequently associated with tree failure and thus identify trees and forests with high vulnerability (Hanewinkel et al., 2010). Those highly vulnerable forests can then be specifically managed to prevent or reduce potential further storm damage (Gardiner and Quine, 2000).

Empirical models are used for analyzing the statistical association between observed storm damage and environmental conditions such as topographic exposure, soil characteristics and wind climate (Hanewinkel et al., 2011). Other statistical associations which are frequently found to be influential on damage occurrence are tree height,

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tree species and recent thinnings (Albrecht et al., 2012; Cremer et al., 1982). Empirical models deliver an estimated probability of storm damage for forest stands (Lanquaye-Opoku and Mitchell, 2005) or individual trees (Xi et al., 2008) and have been developed predominantly for the analysis of single damaging events. There is debate whether such event-specific models may be used to estimate a general susceptibility of forested landscapes. Consequently, current research in empirical storm damage modeling focuses on coupling wind models with storm damage models (Albrecht et al., 2013; Jung et al., 2016) to improve the transferability of those models to generalize damage patterns into event-unspecific risk maps (Schindler et al., 2012).

Many different approaches have been tested to analyze the correlation between wind speed data and forest storm damage. Although this correlation is obvious it appears surprisingly difficult to appropriately represent it quantitatively in models. For a winter cyclone in Germany in 1999, a statistical approach was presented estimating a proxy for the unavailable meteorological wind speed data: using a spatial trend function on geographical coordinates, a smoothed surface of risk values was calculated (Schmidt et al., 2010). The statistically created surrogate served as a realistic representation of the storm track and windfield, but is limited in its meteorological interpretability. Another approach used radar-measured wind speed data (Schütz et al., 2006), but correlations between damage and wind speed were unplausible or non-significant. More encouraging results came from the coupling of an established wind speed model named WAsP (Troen and Lundtang Petersen, 1989) with an established wind risk model (Hale et al., 2015). Also using WAsP, but additionally applying the two wind speed models SAFRAN and ARPS a study in French forests found non-significant but positive correlations between modeled wind speed data and observed storm damage for empirical statistical models (Kamimura et al., 2016). In this study the great difficulty of using the appropriate reference height above ground for calculating wind speed data and the limited spatial resolution of measured and modeled wind data became very clear.

To improve the understanding of the relationship between gust speed and event-specific and event-unspecific empirical storm damage, we developed new empirical models explaining damage at the tree level. We associated gust speed data as modeled by two high-resolution wind models with storm damage observed on long-term forest growth and yield plots (Albrecht et al., 2012) to evaluate (1) the relative importance of gust speed for explaining observed tree damage, (2) the performance of storm event-unspecific damage models compared to storm event-specific models.

## 2. Material and methods

### 2.1. Tree storm damage data

We used data from 1122 long-term forest growth and yield plots located in the German southwestern federal state of Baden-Württemberg. The long-term plots have an average size of 0.24 ha and are irregularly distributed in the study area (Fig. 1). They were initially established to observe tree growth reactions to silvicultural treatments. For this purpose, diameter and height of trees on these plots were measured on average every five years. Tree mortality was monitored and the reason for the mortality was assessed at the individual tree level. Empirical storm damage models have previously been developed based on these data (Albrecht et al., 2012, 2013), but always showed deficiencies in the representation of wind speed.

During the observation period 1979–2006, the two severe storm events “Vivian” (27th February 1990) and “Wiebke” (28th February 1990) which closely followed each other hit Central Europe and were treated as one single event (E1) since it was not possible to distinguish the tree damage between these two storm days. However, in terms of wind speed, Wiebke was exceptionally more intense in the study area than Vivian. Therefore, the gust speed (*gs*) field associated with Wiebke was used as a predictor for damage. During E1 79,260 trees were observed, 2045 of these were storm-damaged trees representing a 3% damage level (Table 1). These 2045 damaged trees were coded as event (1), the other 77,215 as non-event (0).

High-impact storm “Lothar” (26th December 1999) that hit Central Europe including Baden-Württemberg is the second event (E2) that was analyzed. During this storm 98,490 trees were observed in total of which 10,456 trees were storm-damaged, corresponding to a 12% damage level. The datasets E1 and E2 will subsequently be referred to as event-specific.

Together with some additional endemic damage observations (3040) that were caused by minor storm events during the entire study period 1979–2006, storm damage associated with E1 and E2 was merged into a third dataset representing total storm damage in the research plots for the period 1979–2006 (E3). From the total of 532,826 tree observations 15,541 were coded as damaged and 517,285 as undamaged. This dataset will be subsequently referred to as event-unspecific.

*Picea abies* (Norway spruce) and *Pseudotsuga menziesii* (Douglas fir) are the most frequent tree species in the data and also have the highest numbers of damaged trees. While *Picea abies* was the most heavily damaged species from the first storm E1 (5%), *Pseudotsuga menziesii* suffered the greatest damage among all species from E2 (17%). Only a few observations – and these were the least damaged trees – were found in *Quercus petraea* (Pedunculate Oak) and *Quercus robur* (Sessile Oak).

### 2.2. Predictor variables

Variables for the prediction of storm damage were available on the tree and stand level (Table 2). Tree variables comprise species, height and trunk diameter at breast height measured at 1.3 m above ground. In some cases the species *Fagus sylvatica* and *Quercus spec.* had to be regrouped, since differences between the species were not statistically significant. From tree height (*h*) and diameter (*d*), the relative *h/d*-ratio was calculated by dividing a tree’s absolute *h/d*-ratio by the stand’s mean *h/d*-ratio to account for species and age trends. On the stand level, time-invariant variables describe terrain and soil properties such as topographic exposure, elevation, restricted rooting depth and potentially waterlogged soils. Topographic exposure was quantified by the topographic exposure index (topex, Quine and White, 1998; Wilson, 1984) and assessed by measuring the angle of elevation in degrees from a fixed point to the horizon and summing this angle for eight compass directions. It was calculated based on a digital terrain model using a fixed distance to the horizon of 1000 m. Restricted soil rooting depth is a binary variable based on soil mapping which was coded with the value 1 if a significant impediment to rooting such as a heavily compacted clay layer was found within the upper 30 cm of a soil horizon. This restricted rooting depth may indicate difficult rooting conditions for trees and thus reduced anchorage moments. A very similar potential effect of destabilization of tree rooting is coded in the binary variable soil waterlogging which was attributed the value 1 if soils showed signs of waterlogging or stagnant water, leading to impeded rooting due to lack of oxygen in the soil.

Time-variant variables at the stand-level describe the density of the forest stands as quantified by the number of stems per hectare, the intensity and other characteristics of thinning operations. The thinning quotient of scheduled removals was calculated as the mean quadratic diameter of removed trees divided by the mean quadratic diameter of all trees prior to thinning. Greater values thus indicate the removal of more dominant trees within a stand. To quantify the intensity of a thinning, the amount of wood volume removed by a thinning intervention was calculated. Only those trees were considered which were thinned in a scheduled or regular manner, not salvaged trees. In general, stand-level variables referring to dominant values are based on using the average for the 100 largest diameter trees per hectare.

Variables for gust speed (*gs*) originate from two different *gs* models (G). The first model (G1) is the nonhydrostatic Karlsruhe Atmospheric

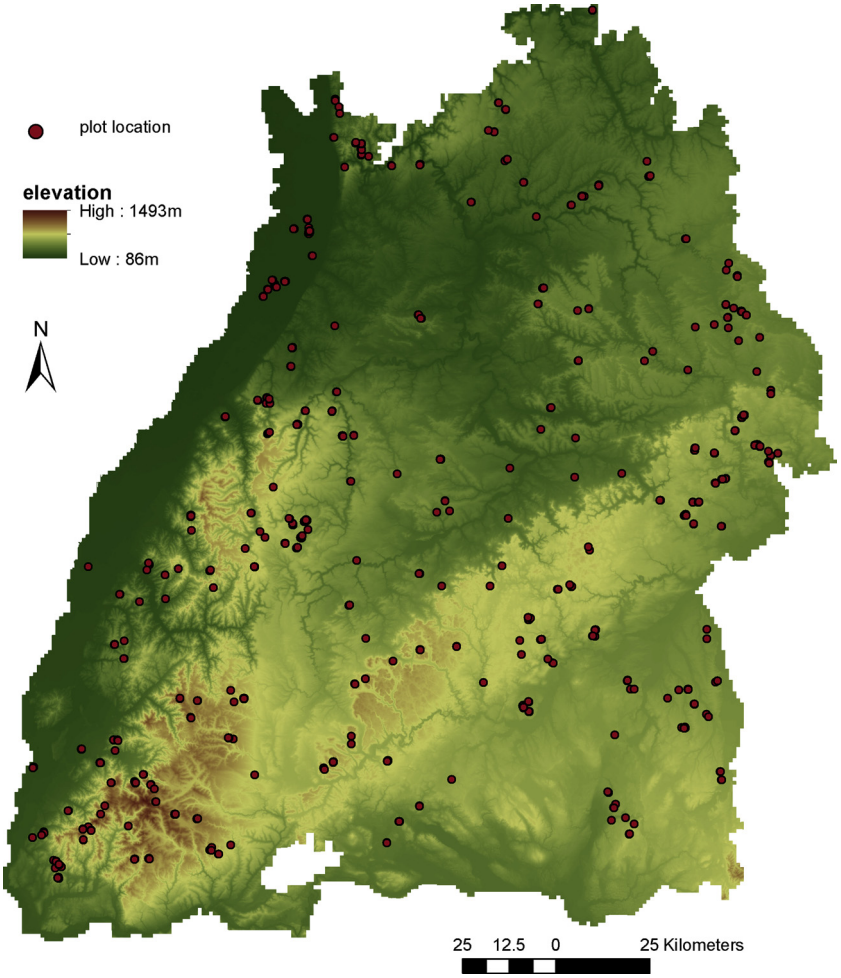


**Fig. 1.** location of the analyzed growth and yield plots in Southwest Germany.

**Table 1**
Storm damage stratified as tree numbers by storm event (E1-E3) and tree species. U: Undamaged trees, D: Damaged trees, D (%): damaged trees as percentage of U + D.

| | E1 | | | E2 | | | E3 | | |
|---|---|---|---|---|---|---|---|---|---|
| Tree species | U | D | D (%) | U | D | D (%) | U | D | D (%) |
| *Abies alba* | 4,190 | 17 | 0 | 5,765 | 499 | 8 | 27,171 | 637 | 2 |
| *Fagus sylvatica* | 6,756 | 24 | 0 | 5,538 | 693 | 11 | 42,183 | 778 | 2 |
| *Larix decidua, L. kaempferi* | 4,728 | 19 | 0 | 2,732 | 132 | 5 | 25,706 | 188 | 1 |
| *Picea abies* | 27,500 | 1,507 | 5 | 41,076 | 4,139 | 9 | 208,485 | 6,941 | 3 |
| *Pinus sylvestris* | 3,719 | 6 | 0 | 3,796 | 70 | 2 | 34,697 | 174 | 0 |
| *Pseudotsuga menziesii* | 29,902 | 472 | 2 | 28,414 | 4,911 | 15 | 174,417 | 6,810 | 4 |
| *Quercus robur, Q. petraea* | 420 | | 0 | 713 | 12 | 2 | 4,626 | 13 | 0 |
| | 77,215 | 2,045 | 3 | 88,034 | 10,456 | 11 | 517,285 | 15,541 | 3 |

Mesoscale Model (KAMM) which provides fields of maximum *gs* with a spatial resolution of 1000 m × 1000 m. It is a three-dimensional non-hydrostatic numerical simulation model that describes atmospheric processes on the basis of equations of physics with a terrain following coordinate system. It is driven by a large-scale basic state which is given geostrophically and hydrostatically. The input data required to drive the model includes large-scale meteorological data, elevation data and roughness information in the study area. More details on the model can be found in Adrian (1994) and Kalthoff et al. (2003). The model was operated by the developers and the resulting data were provided to the authors of this paper.

The second model (G2) is a statistical *gs* model which was developed by Jung and Schindler (2015, 2016). The model is based on daily maximum *gs* time series measured at stations of the German Meteorological Service in the period 1979-2013. G2 simulates *gs* with an LSBoost approach (Friedman, 2001) at a spatial resolution of 50 m × 50 m as a function of sector- and distance-limited surface roughness, terrain-related variables and ERA-Interim wind speed (Dee et al., 2011) at the 850 hPa air pressure level. Surface roughness was estimated from Corine Land Cover data available for Germany (UBA, 2009) as roughness lengths according to Jung and Schindler (2015). The terrain-related features elevation, aspect, curvature and slope, topographic exposure (Quine and White, 1998; Wilson, 1984) were derived from a digital terrain model following Jung and Schindler (2016).

Both models were used to simulate *gs* associated with E1 ($G1_{E1}$, $G2_{E1}$), E2 ($G1_{E2}$, $G2_{E2}$) and an event-unspecific 50-yr return period. The 50-yr return period values of *gs* were applied as the predictor variable for storm damage associated with E3 ($G1_{E3}$, $G2_{E3}$). For

**Table 2**
Descriptive statistics of candidate predictor variables for the research plots. *gs*: gust speed, *G*1 and *G*2 refer to two different gust speed models. E1 to E3 refer to three different storm events or reference periods for storm damage data.

| Variable | Unit | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Tree species | – | – | – | – | – |
| Tree diameter | cm | 22.6 | 10.3 | 7.0 | 116.8 |
| Tree diameter rank | – | 0.5 | 0.3 | 0.0 | 1.0 |
| Tree height | m | 20.3 | 6.6 | 2.1 | 57.4 |
| Dominant stand height | m | 23.1 | 6.3 | 9.2 | 53.1 |
| Stand mean H/D-ratio | – | 0.93 | 0.14 | 0.46 | 1.56 |
| Stand dominant H/D-ratio | – | 0.73 | 0.09 | 0.45 | 1.06 |
| Relative tree H/D-ratio | – | 1.0 | 0.2 | 0.1 | 4.0 |
| Stand stem density | n/ha | 987 | 668 | 100 | 4,532 |
| Stand basal area | $m^2$/ha | 32.3 | 9.5 | 4.0 | 77.4 |
| Stand volume | $m^3$/ha | 384.7 | 181.8 | 22.8 | 1,844.2 |
| Plot size | ha | 0.24 | 0.13 | 0.03 | 1.50 |
| Scheduled removals | $m^3$/ha | 38.7 | 40.0 | 0.0 | 401.9 |
| Cumulative relative removals | % | 0.33 | 0.16 | 0.00 | 0.85 |
| Thinning quotient | – | 0.80 | 0.24 | 0.00 | 2.73 |
| *G*1-calculated *gs* for E1 | m/s | 35.8 | 3.8 | 19.4 | 49.8 |
| *G*1-calculated *gs* for E2 | m/s | 35.8 | 3.5 | 19.7 | 53.0 |
| *G*1-calculated *gs* for E3 | m/s | 38.0 | 3.0 | 28.2 | 54.7 |
| *G*2-calculated *gs* for E1 | m/s | 31.7 | 5.4 | 18.1 | 47.4 |
| *G*2-calculated *gs* for E2 | m/s | 30.9 | 7.0 | 13.8 | 49.3 |
| *G*2-calculated *gs* for E3 | m/s | 31.9 | 4.3 | 19.7 | 45.4 |
| Topographic exposure | | 17.4 | 26.5 | −26.0 | 205.0 |
| Elevation | m | 565 | 220 | 104 | 1,246 |
| Free $CaCO_3$ (yes: 1, no: 0) | – | 0.11 | 0.31 | 0.00 | 1.00 |
| soil waterlogging (yes: 1, no: 0) | – | 0.07 | 0.25 | 0.00 | 1.00 |
| Heavy acidity (yes: 1, no: 0) | – | 0.20 | 0.40 | 0.00 | 1.00 |
| Restricted soil rooting depth (yes: 1, no: 0) | – | 0.08 | 0.27 | 0.00 | 1.00 |

simplification and abbreviation the gust models are referred to with the letter *G* and the storm events with the letter E from here on.

### 2.3. Statistical models

Since the choice of model type has an impact on variable selection, importance ranking and model performance, generalized linear models (GLM) as well as Random Forest models (RF) were fit to the data. Both types of models are suited for the analysis of binary response variables, but they differ significantly in their modeling approaches.

GLMs have been used to analyze binary response data for a long time in epidemiological studies (Hosmer and Lemeshow, 2000) and have been transferred to model mortality events in forestry as well (Hanewinkel et al., 2008, 2010; Valinger and Fridman, 1997). GLMs reproduce the relationship between response and predictors in monotonous linear or curvi-linear form and thus display general relationships. Compared to techniques with closer data fitting such as boosted regression trees, GLMs may show weaker fit statistics (Nakou et al., 2015). However, this disadvantage is at the same time an advantage, since model and effect interpretation is straightforward. Basic GLMs have been extended to accommodate spatial and temporal autocorrelation with random effects and autocovariates (Dormann, 2007; Pinheiro and Bates, 2000; Zuur et al., 2009). Interaction effects may also be specified, similarly to linear models, to improve the adequacy of the predictors-outcome relationship.

The GLM development in our study consisted of (1) identifying and removing correlated variables, (2) variable selection, and (3) model assessment. If strongly correlated (Pearson correlation coefficient > 0.7) candidate predictors were detected, one of the two respective predictors was eliminated. The choice of removing one of the two correlated predictors was based on biological plausibility.

For variable selection we applied a simple so-called purposeful selection technique (Hosmer and Lemeshow, 2000). In this selection approach, biological considerations are more strongly considered and expressed as a preselection of meaningful and plausible predictors compared to automatic variable selection. Examples of such biological considerations can be that mortality should increase with the age of trees and not with their diameter, or that growth rates should depend on soil and climate variables rather than altitude as a proxy. We selected the purposeful approach for two reasons: (1) Stepwise forward or backward variable selection have been criticized to be deterministic and thus too inflexible and technical (Hosmer and Lemeshow, 2000); (2) we have prior knowledge and experience with the analyzed data (Albrecht et al., 2013).

The GLMs were fitted in the statistical software R (R Core Team, 2016) using the base function 'glm'. Since there is not a genuine statistic for quantifying the relative importance of predictors in GLMs, we used the z-statistic associated with the estimated coefficient of each predictor. The z-statistic quantifies the standard deviation of a coefficient's maximum likelihood estimate and we calculated the relative z-statistic for each predictor in each model as a surrogate for a predictor's relative importance.

RF models are a more recent method and consist of repeatedly fitting many independent individual decision trees. During the process of fitting the RF models, the data are repeatedly split into dissimilar groups for one predictor at a time (node or split), aiming to discriminate between events and non-events as clearly as possible with threshold values for a split. These splits or nodes are then repeated to subdivide a branch and to finally assemble an entire decision tree. Frequently, deviance is used as a split decision criterion. When fitting a RF model using only one predictor, a dataset may successively be divided into many different subgroups based on different threshold values of the same predictor. However, it is more common to use several predictors for RF model fitting.

RF models belong to a group of machine learning methods referred to as classification and regression trees and have recently been applied in forestry and ecological studies covering a wide area including genetic studies (Díaz-Uriarte and de Andrés, 2006), species distribution modeling (Bittner et al., 2011; van der Maaten et al., 2017) and estimating timber volume in forests (Latifi et al., 2010). RF models have great capacities to accommodate dependent observations, multicollinear predictors, outliers and missing values without dropping the observation. They intrinsically represent potentially interactive effects by the hierarchical arrangement of the split criteria in the decision trees (Breiman, 2001). These features make RF models distinctly different from GLMs and thus we selected them as the second type of statistical model for our analysis. The results of this non-parametric method are data-specific predictor importance estimates, which were converted to relative importance estimates by dividing predictor importance estimates by the sum of all predictor importance estimates. The predictor variable selection was carried out in the same way as for the GLMs. The RF analyses were performed using the Matlab software (MATLAB and Statistics Toolbox (Release, 2017)) with a minimum leaf size of 100 observations, 10 surrogate splits at each node and the square root of the total number of predictors used in the model as the number of predictor variables randomly sampled at each node. The RF models were built on 63% and tested on 37% of the data.

When using the word "model" subsequently, we predominantly refer to the aforementioned statistical models and not to the wind speed models. Only the output *gs* values of the wind speed models were tested as predictor variables.

In the GLMs, parsimonious base models were fitted without any information on *gs*. In the next step, *gs* was added to quantify the changes in the models' fit statistics.

For both GLMs and RFs, models were fit to the events E1 and E2 separately and then additionally to the entire reference period E3. A comparison of the associated goodness of fit statistics allows the interpretation whether it is reliable and reasonable to model storm risk over the long-term in an event-unspecific manner (E3), or if it is necessary to model storm events individually (E1, E2).

To assess model performance, the area under the receiver operating

characteristic (ROC) curve (AUC) was used (Hosmer and Lemeshow, 2000). It is a common measure for performance and fit of models with binary responses (Peterson et al., 2007). The AUC value is scaled between 0 and 1 with 1 indicating perfect discrimination and 0.5 indicating no capability to discriminate. In addition, the model accuracy was quantified for the RF models as (correctly classified events + correctly classified non-events) / total observations. Model accuracy is an easy to interpret measure of the goodness of a model fit and was originally developed for logistic regression (Hosmer and Lemeshow, 2000) but can be also applied to RF models. Additionally we calculated the success index for the RF models, which is another measure of model performance especially suited for datasets with one level of the response variable being much more frequent than the other (Hale et al., 2015), in this case no damage. Success index was calculated as 0.5*(correctly classified events / observed events + correctly classified non-events / observed non-events). Model accuracy and success index were only needed for the RF models to verify unexpectedly high AUC values.

In addition to quantifying the relative importance of *gs* with the z-statistic and RF-related relative importance measures, AUC of several model fits was calculated: (1) In a backward selection mode *gs* was removed from the models including all significant predictors to calculate the loss in model performance; (2) Additionally, topex was removed from the models obtained in step 1; (3) in a forward selection mode we started from a null model and calculated a series of models containing only one predictor at a time. The difference of AUC values then indicates losses (1, 2) and gains (3) of model performance when removing and introducing the respective predictors.

This modeling approach yielded 12 models per event, thereof 6 GLMs and 6 RF models, totaling for all three events 36 model fits.

## 3. Results

### 3.1. Contribution of gust speed (gs) data in models using only one predictor

The first visual assessment of the differences in *gs* between damaged and undamaged trees did not show great differences (Fig. 2). Only for E2 and E3 there was a slight trend for damaged trees being exposed to higher *gs* for G2. For the individual events E1 and E2 *gs* model G2 had generally lower *gs* values compared to G1.

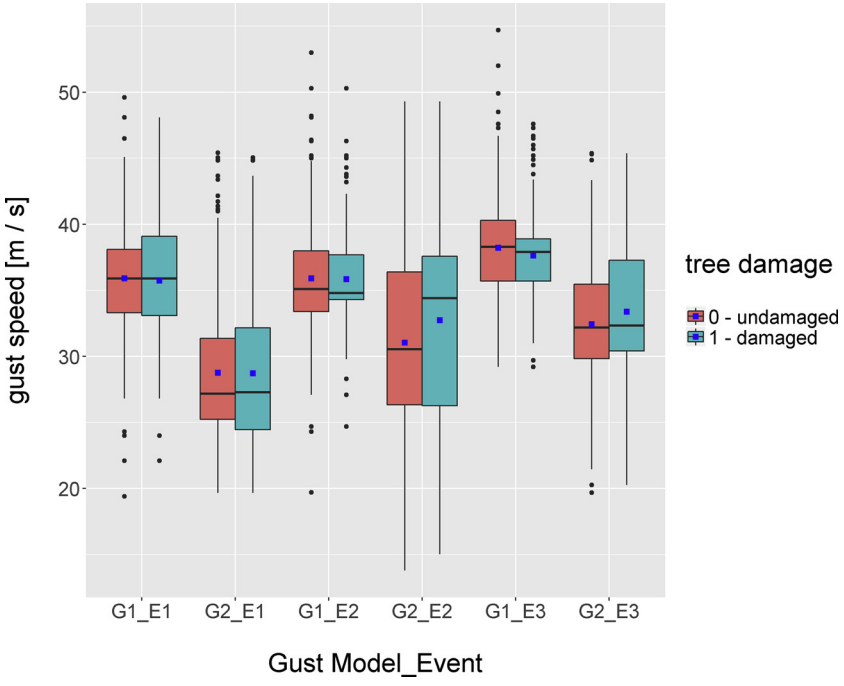


**Fig. 2.** Boxplot comparison of gust speed for damaged and undamaged trees. Results are displayed for the gust speed models G1 and G2 and seperately for the three damage events E1 - E3. Box center lines mark the median, blue squares the mean value. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

**Table 3**
Model performance as quantified by AUC of models using only one predictor for E1-E3. Models were not calculated (empty cell) if predictors were not selected in the models using all significant predictors.

| Predictor variable | E1 GLM | E1 RF | E2 GLM | E2 RF | E3 GLM | E3 RF |
|---|---|---|---|---|---|---|
| *G1 gs* | 0.6263 | 0.9640 | 0.5789 | 0.9096 | 0.5625 | 0.8400 |
| *G2 gs* | 0.7367 | 0.9922 | 0.6469 | 0.9613 | 0.5613 | 0.9121 |
| scheduled removals | 0.7400 | 0.9876 | 0.5831 | 0.9213 | 0.6287 | 0.9158 |
| cumulative relative removals | | | 0.5992 | | 0.5618 | |
| topex index | 0.6185 | 0.8646 | 0.5381 | 0.7442 | 0.5450 | 0.7174 |
| tree diameter rank | 0.5029 | | 0.5074 | | 0.5148 | |
| tree height | 0.7154 | 0.6819 | 0.6264 | 0.6519 | 0.6438 | 0.6547 |
| thinning quotient of scheduled removals | 0.8512 | | 0.7172 | | 0.7819 | |
| tree species | 0.7143 | 0.6898 | 0.5941 | 0.5863 | 0.5900 | 0.5588 |
| tree species - tree height interaction | | | 0.6932 | | 0.7062 | |

Assessed with statistical models the influence was clearer. For the GLMs, the thinning quotient was the predictor with highest AUC values for E1-E3 (Table 3). For E1, *gs* yielded the second best model using only one predictor (AUC = 0.74) while for the other two reference periods, models using *gs* as the only predictor ranked in the middle. Another interesting finding was that the linear effect of *gs* on storm damage was negative for E1 for both G1 and G2 (Table S1, supplementary material). The same negative correlation was found for E3 using G1.

In the RF models based on only one predictor, models using *gs* systematically ranked highest for all three events, all with AUC > 0.9 (Table 3). For E1, AUC = 0.99 was attained using *gs* estimated with G2. Equally high ranked was the RF model using scheduled removals as the only predictor. Interestingly, there were only slight AUC differences between RF models and GLMs for the models using only species or height as predictors, respectively.

### 3.2. Relative importance of gust speed (gs) in models using all significant predictors

In the GLMs built for E3, *gs* had small relative importance of 7% and

**Table 4**
Relative importance for the predictors and overall fit statistics in the generalized linear models (GLM) and random forest (RF) models. AUC is the area under the ROC curve, Δ is the difference between models not using gust speed as a predictor variable (baseline model), models using gust speed as a predictor variable, and models using neither gust speed nor topex as predictor variables.

| | | | relative importance [%] | | | | | | | Fit statistics | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Event | statistical model | gust speed model | scheduled removals | topex | diameter rank | tree height | interaction species - height | tree species | gust speed | AUC | Δ [%] | Accuracy | Success index |
| E1 | GLM | None | 4 | 22 | 9 | 30 | – | 36 | – | 0.9485 | | | |
| | GLM | None | 3 | – | 10 | 37 | – | 50 | – | 0.9303 | −1.96 | | |
| | GLM | *G1* | 2 | 20 | 8 | 29 | – | 22 | 19 | 0.9519 | 0.36 | | |
| | GLM | *G2* | 5 | 16 | 6 | 20 | – | 35 | 18 | 0.9594 | 1.15 | | |
| | GLM | *G1* | – | – | – | – | – | – | 100 | 0.6263 | | | |
| | GLM | *G2* | – | – | – | – | – | – | 100 | 0.7367 | | | |
| | RF | None | 30 | 29 | – | 19 | – | 22 | – | 0.9923 | | 0.9881 | 0.9674 |
| | RF | None | 30 | – | – | 33 | – | 37 | – | 0.9816 | −1.10 | 0.9866 | 0.9584 |
| | RF | *G1* | 18 | 20 | – | 14 | – | 16 | 32 | 0.9955 | 0.32 | 0.9893 | 0.9779 |
| | RF | *G2* | 25 | 16 | – | 13 | – | 12 | 34 | 0.9956 | 0.33 | 0.9899 | 0.9714 |
| | RF | *G1* | – | – | – | – | – | – | 100 | 0.9640 | | 0.9807 | 0.9091 |
| | RF | *G2* | – | – | – | – | – | – | 100 | 0.9922 | | 0.9879 | 0.9854 |
| E2 | GLM | None | 26 | 18 | – | 14 | 19 | 24 | – | 0.8641 | | | |
| | GLM | None | 29 | – | – | 17 | 25 | 29 | – | 0.8645 | 0.04 | | |
| | GLM | *G1* | 22 | 16 | – | 13 | 16 | 19 | 14 | 0.8685 | 0.51 | | |
| | GLM | *G2* | 21 | 8 | – | 11 | 17 | 21 | 22 | 0.8707 | 0.76 | | |
| | GLM | *G1* | – | – | – | – | – | – | 100 | 0.5789 | | | |
| | GLM | *G2* | – | – | – | – | – | – | 100 | 0.6469 | | | |
| | RF | None | 29 | 21 | – | 31 | – | 18 | – | 0.9576 | | 0.9461 | 0.8840 |
| | RF | None | 26 | – | – | 38 | – | 36 | – | 0.9378 | −2.11 | 0.9292 | 0.8549 |
| | RF | *G1* | 17 | 15 | – | 21 | – | 12 | 35 | 0.9584 | 0.08 | 0.9530 | 0.8913 |
| | RF | *G2* | 16 | 19 | – | 21 | – | 16 | 28 | 0.9691 | 1.20 | 0.9561 | 0.8945 |
| | RF | *G1* | – | – | – | – | – | – | 100 | 0.9097 | | 0.9100 | 0.7742 |
| | RF | *G2* | – | – | – | – | – | – | 100 | 0.9613 | | 0.9509 | 0.8850 |
| E3 | GLM | None | 13 | 13 | 9 | 6 | 29 | 30 | – | 0.8672 | | | |
| | GLM | None | 15 | – | 11 | 6 | 33 | 35 | – | 0.8669 | −0.03 | | |
| | GLM | *G1* | 13 | 12 | 9 | 5 | 27 | 28 | 7 | 0.8692 | 0.23 | | |
| | GLM | *G2* | 11 | 10 | 9 | 5 | 29 | 26 | 10 | 0.8669 | −0.03 | | |
| | GLM | *G1* | – | – | – | – | – | – | 100 | 0.5625 | | | |
| | GLM | *G2* | – | – | – | – | – | – | 100 | 0.5613 | | | |
| | RF | None | 23 | 24 | – | 28 | – | 25 | – | 0.9633 | | 0.9688 | 0.9101 |
| | RF | None | 31 | – | – | 33 | – | 36 | – | 0.9360 | −2.92 | 0.9733 | 0.8916 |
| | RF | *G1* | 31 | 16 | – | 21 | – | 7 | 24 | 0.9684 | 0.53 | 0.9733 | 0.9106 |
| | RF | *G2* | 26 | 18 | – | 20 | – | 13 | 22 | 0.9702 | 0.71 | 0.9729 | 0.9107 |
| | RF | *G1* | – | – | – | – | – | – | 100 | 0.9002 | | 0.9678 | 0.8500 |
| | RF | *G2* | – | – | – | – | – | – | 100 | 0.9734 | | 0.9680 | 0.8456 |

10% for G1 and G2 (Table 4). For E1, G1- and G2-related relative importances were 19% and 18%, respectively. The largest relative importance was found for G2_E2 (22%). Within the GLMs, relative importance of *gs* was higher for the event-specific models E1 and E2, compared with event-unspecific models E3. The relative importance of species was higher than *gs* in all but one case.

In the RF models, relative importance of *gs* was much higher compared to the GLMs. The minimum relative importance was 22% for G2_E3 and increased to 35% using G2_E2. Relative importance of *gs* was higher for the event-specific models (E1, E2) than for the event-unspecific models (E3). Compared to the other predictor variables, *gs* was the single most important predictor variable, except for the RF model for G2_E3 (relative importance = 22%). In this case, scheduled removals ranked slightly higher (relative importance = 26%).

Model performance of all models using all significant predictors was very high as expressed by AUC values between 0.86 and 0.99, and was improved in all but one case when introducing *gs* data. However, the improvements were in all cases very small. In both GLM and RF modeling techniques, the AUC values improved more strongly when introducing G2, compared to introducing G1-calculated *gs* to the models using all significant predictors. One exception was found in the GLM for E3, where the introduction of G1 yielded a small model improvement while G2 actually led to a slight decline of the AUC from 0.8672 to 0.8669.

When removing both *gs* and topex from the models using all significant predictors, the relative loss of model performance was relatively small (-0.03 to -2.92%) but in most cases greater than the performance gain when introducing *gs*. One exception occurred in the GLMs for E2, where AUC improved by 0.04% when removing topex (Table 4), while the AIC worsened (higher values, Table S1).

Comparing the two *gs* sources with models using only one predictor we found systematically higher AUC values using G2 as *gs* predictor. For example, the respective GLM results using G1_E1 had AUC = 0.63 while the same model using G2 yielded AUC = 0.74 (Table 3). Only for the GLMs of E3 the two data sources yielded very similar model performance (AUC = 0.5613, 0.5625, Table 3).

Model accuracy and success index values for the RF models were proportional to the AUC values (Table 4) and confirmed the findings based on AUC values.

### 3.3. Storm event-unspecific vs. storm event-specific models?

In general, the event-specific models built for E1 performed noticeably better than the corresponding event-unspecific models built for E3, based on higher AUC values for both GLMs and RF models and on higher accuracy and success index for RF models. For E2, the result was inconsistent since the AUC, accuracy and success index values were in some cases lower, in some cases higher than those of the corresponding event-unspecific models built for E3. In general it has to be noted that especially the RF models performed exceptionally well with values > 0.95.

Another indication is given by the relative importance of *gs*, whose values were systematically higher for the event-specific models. For example, the RF model using G2_E3 yielded a relative importance of

22%, while the event-specific models built using G2_E1 and G2_E2 showed corresponding values of 34% and 28%, respectively.

## 4. Discussion

### 4.1. Differences between the modeling techniques

The most prominent differences between RF models and GLMs were found for the models based on one predictor only, when using *gs*. The RF models attributed outstanding predictive power to *gs* while the GLMs quantified moderate impact, comparable to that of other predictors such as tree height and scheduled removals. This difference may be attributed to the characteristics of RF models, since they are based on decision tree logic using split criteria and threshold values. Establishing a decision tree using one predictor only, a dataset may successively be divided into many different subgroups based on different threshold values. As a consequence, non-linear and non-monotonous effect curves may be extracted. This great advantage allows very close data fitting and may help detecting unusual effect patterns, such as empirical threshold values. However, for effects which may be expected to be more linear or smoothly trend-like, this technique has some limitations, especially when applied in models using one predictor only. A famous example illustrating this problem of decision tree techniques is the problem it has representing a simple 1:1 line (Elith et al., 2008). We conclude that non-linear effects of *gs* on storm damage were better captured by the RF models and that some implausible results of GLMs (negative coefficients of *gs* predictors for E1) could be cross-checked with the RF models by extracting partial effect curves for the predictor *gs*. To do this, however, would require performing regression tree analysis, not decision tree analysis as applied in our approach.

Another remarkable difference between RF models and GLMs was the generally better RF model performance. Although techniques are available to restrict model depth and complexity by pruning and defining a minimum pocket size for branch ends in single decision trees (Hastie et al., 2001), limiting the possible complexity is not recommended for RF models, since they intrinsically avoid over-fitting due to bagging and bootstrapping (Breiman, 2001). We thus attribute this advantage of RF models to not restricting model complexity in combination with their capability of depicting non-linear effect patterns.

These considerations may raise the question if GLMs are at all appropriate for modeling storm damage based on *gs* data any longer. Although this was not the primary question of our study we still see the great advantage of GLMs in their straightforward interpretability. GLMs may identify monotonous linear or curvilinear effects. When applied with care these models may help to represent trends over large areas in a comprehensive manner. Even in direct comparison with modeling techniques capable of identifying non-linear trends or abrupt threshold values such as RFs, Boosted Regression Trees – which are methodologically closely related to RF models – or Generalized Additive Models, GLMs may have similar or better model performance and fit statistics (Elith and Graham, 2009; Nakou et al., 2015). They may also be equally capable of accounting for undesired collinearity as tree-based classification methods are (Dormann et al., 2013). Taking into consideration that spatial and temporal correlation may be accounted for in GLMs by incorporating random effects (Zuur et al., 2009) makes GLMs a robust and powerful model type while classification and regression tree techniques have been criticized to be less robust for predictions (Nakou et al., 2015). Besides these quantitative arguments, also qualitative considerations concerning the trade-offs between generality and accuracy may make GLMs superior to techniques with closer data-fitting capabilities (Guisan and Zimmermann, 2000), depending on the intended model application. This argument is a quite strong argument for our study, since we would have to assume that storm damage increases monotonously with increasing *gs*. This effect could actually have the shape of a saturation curve in curvilinear form. In conclusion, the simplicity of a GLM or a poorer fit statistic should not be used as general arguments against its use.

### 4.2. Relationship between gust speed (gs) data and storm damage

Storm damage was positively associated with *gs* in the GLMs for E2 and E3, but negatively associated with E1. Had this implausible negative correlation been found for all three events, it could have been hypothesized that generally wind-exposed sites lead trees to acclimate to windy climates and reattribute their resources more into diameter than into height growth. This growth stabilization process is known as thigmomorphogenesis and has been extensively reported before (e.q. Telewski, 1995). However, this explanation is weak in our case, since we found positive associations between *gs* and storm damage for E2 and E3. One realistic explanation for this phenomenon is that high *gs* and resulting damage during E1 were actually observed over several days. We used *gs* of the day with the highest average *gs* values. But since the exact day of damage during this multi-day damage event E1 was not recorded for each tree individually, the *gs* of the wrong day could have accidentally been attributed to a tree. Unfortunately, there are no means to verify or further analyze this potential explanation of this finding.

Another potential explanation for this unexpected result might be different soil water saturation for E1 and E2. Since we did not possess appropriate candidate predictors with daily resolution, we were unfortunately unable to quantify this effect, although higher water saturation has in general been reported before to destabilize trees by softening the root-soil interface (Dobbertin, 2002; Hautala and Vanha-Majamaa, 2006; Schreiner et al., 1996).

We were expecting topographic exposure to either become an insignificant predictor or to lose importance when introducing *gs* as a predictor. Surprisingly, topographic exposure remained in all GLMs and RF models and only lost relative importance in the E2-related GLM (reduction from 18% to 8%, see Table 4). This finding indicates that topographic exposure carries additional information which is not fully accounted for by the applied *gs* models. This is additionally supported by the finding that the loss in model performance when dropping topex is greater than the performance gain when introducing *gs*. One explanation could be that the same modeled *gs* in a windward and a leeward location may have different local turbulence levels, which can have higher damage, a hypothesis potentially reflected in a local comparison between measured and modeled wind speed above forest canopies in orographically complex terrain (Grant et al., 2015, 2016). Thus, the *gs* models in our study might not sufficiently incorporate local turbulence and fine-scale orographic effects into their algorithms. Regardless of the causal explanation our findings do not support the hypothesis that topex may be used as a proxy variable for unknown wind and gust speed. Clearly, G2 had an advantage since its horizontal resolution of 50 m is much higher compared to the broad 1000 m resolution of G1 and corresponds much better to the size of the forest plot data, which was 0.25 ha on average. The finer spatial resolution of G2 was apparently capable of capturing local wind speed variability more appropriately. Another explanation is related to acclimation of tree growth to the wind climate which is well represented by topographic exposure (cp. Nicoll et al., 2008). This finding clearly suggests that *gs* models for orographically complex terrain may be improved by accounting for topographic exposure more strongly.

Further improving *gs* modeling over forested lands may not only necessitate improved representation of orographically complex terrain but also of local turbulence above forest canopies. The basis for empirical *gs* models are *gs* values from the networks of the national weather services measured exclusively outside forested areas. And since turbulence patterns over forested areas have been shown to differ from turbulence over open-area measurement sites of the national weather services (Finnigan, 2007; de Langre, 2008), more measurements inside

forest stands and above forest canopies appear necessary to calibrate empirical *gs* models.

Another potential explanation why *gs* fields over large areas with complex terrain can still not be perfectly modeled could be that *gs* is only one aspect of wind loading during storms. The wind load associated with the mean wind and the duration of storms may also contribute to storm damage formation in an accumulative manner not represented in a single value of *gs*. Consequently, it should be tested if modified versions of *gs* models could represent such cumulative effects more appropriately.

## 5. Conclusions

The results from this study demonstrate that empirical storm damage models can be successfully linked to *gs* models to explain storm damage. Although they have weaknesses in terms of providing an understanding of the damage process, they are able to identify the most important damage risk factors in order to provide a solid knowledge base for risk reduction and risk avoidance. Therefore, fundamental next steps can be taken to estimate damage probabilities for future storm events under climate change. Based on the comparison between the individual storm events E1 and E2 with the event-unspecific data E3, storm damage models should be established for individual storm events rather than assuming average event-unspecific storminess over longer periods. Potentially, the occurrence of future storm events could be estimated based on surpassing thresholds of air pressure gradients (Giorgi et al., 2004) and deducing geostrophic winds (Beniston et al., 2007). Applying extreme value statistics may be necessary to not only deduce frequencies but also to identify individual storm events and use geostrophic wind speed estimates to couple with forest storm damage models.

Future *gs* modeling could be improved if topographic exposure, orographic effects, and turbulence above forest canopies are better represented. These improvements should enable storm damage models to estimate damage probabilities under altered meteorological conditions as may be expected under climate change (Feser et al., 2015; Mölter et al., 2016).

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2018.12.017.

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